2000-06

Determinants of flight training performance: an analysis of the impact of undergraduate academic background

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http://handle.dtic.mil/100.2/ADA381146

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THESIS

DETERMINANTS OF FLIGHT TRAINING PERFORMANCE: AN ANALYSIS OF THE IMPACT OF UNDERGRADUATE ACADEMIC BACKGROUND

by

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June 2000

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REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	June 2000	Master's Thesis

4. TITLE AND SUBTITLE
Determinants of Flight Training Performance: An Analysis of Undergraduate Academic Background

5. FUNDING NUMBERS

6. AUTHOR(S)
Reis, Paul M.

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Naval Postgraduate School
Monterey, CA 93943-5000

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Asst. Aviation Officer Community Manager (N131V2)
FB2 Navy Annex, Washington, DC 20370

10. SPONSORING / MONITORING AGENCY REPORT NUMBER
N/A

11. SUPPLEMENTARY NOTES
The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

12a. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited.

12b. DISTRIBUTION CODE

13. ABSTRACT *(maximum 200 words)*

This thesis uses pre-commissioning academic and demographic factors, along with flight school performance data to measure pilot success in flight school. The goal is to determine if undergraduate major or school attended affect flight school performance. Measure of effectiveness include: (1) Flight School Completion Status, (2) Aviation Pre-Flight Indoctrination Composite Scores, and (3) Primary Flight Training Composite Scores. Recruitment for naval aviators is focused on individuals with "technical majors," according to present policy of the Naval Recruiting Command. This recruiting philosophy is based on the "Rickover Hypothesis," which postulates that naval officers with technical degrees are superior to naval officers with non-technical degrees. The Logit model showed that aviators with engineering degrees have a statistically greater chance of completing flight school than aviators with non-engineering technical or non-technical degrees. In addition, the results showed an association between academic background and flight school performance. This research justifies the current Navy policy of concentrating aviator recruitment efforts on individuals with technical degrees.

14. SUBJECT TERMS
Aviator Selection, Aviation Flight Training, Classification and Regression Trees, CART, Cross-Validation, Tree, Logistic Regression, Logit

15. NUMBER OF PAGES
76

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UL

NSN 7540-01-280-5500

Standard Form 298 Rev.-89)
Prescribed by ANSI Std. 239-18

Approved for public release; distribution is unlimited

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Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
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ABSTRACT

This thesis uses pre-commissioning academic and demographic factors, along with flight school performance data to measure pilot success in flight school. The goal is to determine if undergraduate major or school attended affect flight school performance. Measures of effectiveness include: (1) Flight School Completion Status, (2) Aviation Pre-Flight Indoctrination Composite Scores, and (3) Primary Flight Training Composite Scores. Recruitment for naval aviators is focused on individuals with "technical majors," according to present policy of the Naval Recruiting Command. This recruiting philosophy is based on the "Rickover Hypothesis," which postulates that naval officers with technical degrees are superior to naval officers with non-technical degrees. The Logit model showed that aviators with engineering degrees have a statistically greater chance of completing flight school than aviators with non-engineering technical or non-technical degrees. In addition, the results showed an association between academic background and flight school performance. This research justifies the current Navy policy of concentrating aviator recruitment efforts on individuals with technical degrees.

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LIST OF ABBREVIATIONS, ACRONYMS, AND SYMBOLS

AI	Aviation Interest
AIC	Akaike Information Criterion
AN	Aviation and Nautical Test
AOC	Aviation Officer School
APC	Academic Profile Code
API	Aviation Preflight Indoctrination
AQR	Academic Qualification Rating
AQT	Academic Qualification Test
ASTB	Aviation Selection Test Battery
BI	Biographical Inventory
CART	Classification and Regression Trees
CNET	Chief of Naval Education and Training
CV	Cross Validation
DMDC	Defense Manpower Data Center
DOR	Drop On Request
FAA	Federal Aviation Administration
FAR	Flight Aptitude Rating
FR&R	Flight Rules and Regulations
GPA	Grade Point Average
LCDR	Lieutenant Commander
MCT	Mechanical Comprehension Test
MCT	Mechanical Comprehension Test
MQC	Mathematics Qualification Code
MVT	Math-Verbal Test
NAA	Not Aeronautically Adaptable
NAMRL	Naval Aerospace Medical Research Laboratory
NASC	Naval Aviation Schools Command
NASCNSS	Naval Aviation Schools Command Naval Standard Score
NFO	Naval Flight Officer
NOM	Not Officer Material
NPQ	Not Physically Qualified
NRC	Naval Recruiting Command
NROTC	Naval Reserve Officer Training Corps
OCS	Officer Candidate School
OLS	Ordinary Least Squares
OMF	Officer Master File
PASS	Primary Academic Standard Score
FPSS	Primary Flight Standard Score
SAT	Spatial Apperception Test
SO	Submarine Officer
SWO	Surface Warfare Officer
TQC	Technical Qualification Code
USNA	United States Naval Academy

EXECUTVE SUMMARY

The Naval Recruiting Command aviator recruiting policy is to obtain college graduates who possess engineering and science degrees. This recruiting philosophy is based on the "Rickover Hypothesis," which postulates that naval officers with technical degrees are superior to naval officers with non-technical degrees. Bowman (1990) examined this hypothesis for officers undergoing nuclear training and found that technical degrees significantly increased the probability of completing this training, but that little effect on subsequent performance and promotion was observed. The current study examines the Rickover hypothesis for student aviators by comparing their academic and flight performance during training. These comparisons are made based on flight school completion/attrition status and on composite scores attained during Aviation Pre-flight Indoctrination and Primary flight training. It is expected that differences in performance will be found based upon undergraduate major or college attended. In addition, differences in performance will be noted based upon scores received on the aviation selection test battery. Individuals who have a higher Academic Qualification Rating and/or a higher Flight Aptitude Rating will perform better during the academic and flight portions of training.

Using Classification and Regression Trees, Logistic regression and Least-Squares regression, the performance of student aviators in the aviation-training pipeline (measured by completion or attrition, and by flight school grades) is modeled. Demographic variables from the officer master file, along with aviation selection test battery performance data, are used as predictors to measure success in flight school. These factors include sex, race,

ethnicity and commissioning source, along with undergraduate major, college attended, and undergraduate academic performance grades.

Classification Tree and Logit models are developed to predict individual success in completing training. Results indicate that academic major is a significant predictor of flight school completion, along with college, race, Aviation Qualification Rating and Flight Aptitude Rating. Engineers are more likely to complete flight school than individuals who hold non-engineering technical or non-technical degrees. Further, graduates from the Naval Academy have a significantly higher completion rate than individuals who attended other colleges.

Regression Tree and Least-Squares regression models are developed to measure relative success of individuals throughout the flight training pipeline by using predictors to model their academic and flight performance grades during Aviation Pre-flight Indoctrination and Primary flight training. Only individuals who successfully completed flight school are considered. Significant predictor variables include Academic Qualification Rating, Flight Aptitude Rating, race, ethnicity, college and major, indicating that each predictor has an influence on the composite score attained while attending flight school.

In summary, there is evidence to suggest that academic major and college attended affect performance in flight school. These factors, along with race, ethnicity, Academic Qualification Rating and Flight Aptitude Rating can be used by the recruiting command to screen potential applicants using the models developed. Individuals can be compared, based on their individual characteristics, to determine the best candidates for acceptance into flight school.

ACKNOWLEDGEMENT

I would like to take this opportunity to thank those individuals who have provided support and encouragement throughout this project. First, a special thanks to LT Loukia Loukopoulos from NOMI, LT Henry Williams from NAMRL, and OSCS(SW) Dave Reed from DMDC for providing assistance in obtaining data files used in this work. I would also like to thank Dr. William K. Krebs for his many insights into the aviation community and for providing focus and direction needed to stay on task. I would like to thank my wife April, who constantly reminded me of the goals I had set. Finally, and perhaps most important, I would like to thank Dr. Sam Buttrey for his diligence, patience and untiring efforts to lead and guide me through the statistical and literary minefield that littered this work. Without his efforts, this thesis would never have been completed.

I. INTRODUCTION

A. BACKGROUND

As the United States makes the transition into the 21st century, changes in the recruiting and selection process for naval aviators could bring an improvement to the Navy's return on investment. The qualification process for aviators is intense, with many applicants competing for a limited number of billets. Many factors contribute to selection failure. First among them are stringent initial screening requirements. The applicant screening process requires all individuals to pass both an Aviation Selection Test Battery (ASTB) and a military physical exam. These initial qualification standards result in a disqualification rate of 75% from the initial applicant pool (Williams, Albert, and Blower, 1999). Further, individuals must then apply for acceptance into the flight-training program, whereupon successful candidates are ordered to flight school for initial and follow-on flight training. Each stage in the qualification process brings about a reduction in the pool of potential aviators, resulting in 1 fleet-qualified aviator for about every 25 applicants (Wahl, 1998).

The aviator recruiting effort is focused on individuals with "technical majors," according to present policy of the Naval Recruiting Command (NRC, 1999). This idea is in line with the "Rickover Hypothesis," which presumes that individuals with technical degrees are better prepared and make better naval officers than individuals with non-technical degrees. However, Bowman (1990) found a very weak statistical relationship between USNA major and fleet performance, using fitness reports and other job performance variables. In addition, he argued that the need for technical skills diminishes as officers advance to positions requiring greater managerial and administrative skills

(Bowman, 1990). Bowman found that although a technical degree significantly affects the likelihood of completing the nuclear training pipeline, little effect on performance and promotion is apparent once individuals complete training and enter the fleet (Bowman, 1990). Performance in areas not directly associated with the formal training process, such as leadership, management, and interpersonal skills, affect overall individual performance and promotion rates, yet have little to do with academic background. Thus, by limiting the potential applicant pool to individuals with technical degrees, a significant portion of the population of potential aviators is removed from consideration. These are individuals who lack a technical degree but might otherwise pass screening requirements, flight school and thus, become Naval aviators.

B. RESEARCH OBJECTIVES

This study examines the effect of academic background on pilot performance within the flight-training pipeline. Each analysis focuses on the effect of academic achievement as measured by grades, undergraduate major, and the correlation between college quality, commissioning source and flight school performance. Comparison between technical and non-technical aviators is made to determine if pilots with technical degrees perform better through the flight-training pipeline.

A second objective was to analyze the effect of undergraduate major on retention and promotion rates of pilots who completed the flight-training pipeline during the 1980's, based upon their flight school performance, and in conjunction with other demographic variables. This, however, was impossible because of incomplete data on flight school aviator performance in years previous to 1990.

C. SCOPE AND LIMITATIONS

The focus of this study is on the effects of undergraduate academic major and college attended on student aviator performance. Effects of other college characteristics, such as participation in athletics or other extracurricular activities, are not included. This intention is to test the validity of the "Rickover Hypothesis" with regard to the aviation community and to provide recruiters with information that will allow them to focus on those college students who are likely to perform well in the aviation community. Academic major and college are included in the models as independent variables. Flight Aptitude Rating (FAR) and Academic Qualification Rating (AQR) are also included since they are designed to predict performance in flight school. Demographic variables such as sex, race, ethnicity and commissioning source are included to control for possible confounding. (For example, if it were the case that black aviators both performed better on average in flight school and were more likely to have technical degrees than non-blacks, the effect of having a technical degree would be over-stated in a model that did not include race as an independent variable.)

This study is limited to pilots who graduated from flight school between 1990 and 1999. Individuals from the United States Naval Academy (USNA), Naval Reserve Officer Training Units (NROTC) or from Officer Candidate School (OCS) are included. The data set does not include those who transferred into the aviation community from another community or from another service. Officers with prior enlisted service are omitted if they served greater than four years in an enlisted capacity.

The most recent revision to the ASTB occurred in 1992. Due to the changeover (further described in Chapter II), it is not yet possible to consider the long-term retention and promotion characteristics of officers who have qualified under the present applicant screening guidelines. Because it takes up to two years from initial test taking to commissioning, and a further two years for individuals to complete their flight training, these officers could only recently have started their obligated service requirement and would not have yet reached time-in-grade requirements for Lieutenant Commander. In fact, most will not have yet completed their initial service requirement. Therefore, it is difficult to predict retention likelihood for these individuals from results found in this study.

D. ORGANIZATION

This study is organized into five chapters. Following the introduction and background contained in Chapter I, Chapter II reviews previous studies and literature related to this area of research. Chapter III describes the data files that are employed for this research. A detailed description of model specifications and an overview of methodology are given, with an explanation of the dependent and independent variables. Chapter IV presents the results from this study using Classification and Regression Trees (CART), Logistic regression and Least-Squares regression. Chapter V offers conclusions and recommendations based on the results of the previous chapter.

II. LITERATURE REVIEW

A. QUALITIES OF AN AVIATOR

Many studies have been conducted that examine the characteristics of "good" aviators; however most have focused on the applicant selection process, rather than measuring skill and performance over the long term. According to the Federal Aviation Administration, "… no one is born a natural pilot. Competent commercial pilots become so through study, hard work and experience" (U.S. Department of Transportation, p. 1, 1995). In order to fly safely, all aviators must master basic airmanship, operation of aircraft systems, and navigation. Commercial pilot tests cover a wide range of subject areas, in addition to specific instruction in the aircraft category for which rating is sought. Military aviators must also master these functional areas, in addition to specialized requirements necessary to work in a combat role. They must also understand the operation of weapon systems and cope with high stresses imposed by operation in combat environments. A list of knowledge areas from the 1995 Commercial Pilot Knowledge Test Guide is given below as suggestions of topics to be covered by rating exams (U. S. Department of Transportation, 1995):

1. The Federal Aviation Regulations that apply to commercial pilot privileges, limitations, and flight operations.

2. Accident reporting requirements of the National Transportation Safety Board.

3. Basic aerodynamics and the principles of flight.

4. Meteorology, including recognition of critical weather situations, wind shear recognition and avoidance, and the use of aeronautical weather reports and forecasts.

5. The safe and efficient operation of aircraft.

6. Weight and balance computation.

7. Use of performance charts.

8. Significance and effects of exceeding aircraft performance limitations.

9. Use of aeronautical charts and magnetic compass for pilotage and dead reckoning.

10. Use of air navigation facilities.

11. Aeronautical decision-making and judgment.

12. Principles and functions of aircraft systems.

13. Maneuvers, procedures, and emergency operations appropriate to the aircraft.

14. Night and high-altitude operations.

15. Descriptions of and procedures for operating within the National Airspace System.

In addition to the above areas, naval aviators must also master the complexities of combat weapon systems and the effects each has when carried and launched. They must understand launch parameters of the weapons, their flight characteristics, and the additional system controls they require. In another area, most naval aviators are faced with the obstacle of landing an aircraft on an unstable platform (ship or aircraft carrier), limited in size, and moving relative to the aircraft. These additional factors are summed up by Pohlman & Fletcher (1999), who state that military pilots must (Pohlman & Fletcher, 1999):

1. Plan the route through space in relation to the intended target, suspected threats, actual threats, other known aircraft, wingmen, and weapons.

2. Monitor the aircraft display for electronic notification of threats.

3. Differentiate among threat displays (these can portray 15 or more different threats).

4. Plan ingress to and egress from the target.

5. Set switches for specific missions during specific periods of the flight.
6. Monitor radio chatter on multiple frequencies for new orders and threat notification.

7. Monitor progress along the planned route.

8. Calculate course, altitude, and airspeed corrections.

9. Plan evasive maneuvers for each type of threat and position during the mission.

10. Plan weapons delivery.

In short, the demands of military (and commercial) flying require the ability to make quick mental adjustments using proper judgment in response to rapidly changing situations. Because of this necessity, assessment procedures to determine qualified candidates for aviator training are rigorous. Proper candidate selection saves time, material and funding, and results in improved quality and operational readiness. Because of the expense and complexity required to train competent pilots, "almost every test in the psychological arsenal has been evaluated at one time or another to determine its applicability for aircrew selection" (Hunter, p. 129, 1989). In addition, Hilton and Dolgin wrote that there may be no other "occupation in the world that benefits more from personnel selection technology than that of military pilot" (Hilton & Dolgin, p. 81, 1991).

According to Pohlman and Fletcher (1999), three conclusions may be drawn from review of studies related to aviator selection. The first is that nearly all validation studies conducted concern the ability to predict performance in training, rather than long-term pilot performance. Inherent in this reasoning is the belief that an aviator who does well in training will continue with good performance throughout his or her career. Training validation is good because it identifies potential failures early, resulting in decreased costs borne by the government or individual trainee. According to Hunter, flight training is "the most expensive of the many training programs conducted by the military services" (Hunter, p. 129, 1989). The second conclusion is that there is little relationship between general intelligence and aviator performance. It was noted that newer tests of mental ability might better identify aspects of general intelligence that predict aviator performance. Finally, Hunter (1989) found that of the 36 studies conducted, "only those concerned with instrument comprehension and mechanical comprehension were consistent predictors of success." In a more recent study by Hunter and Burke (1995), it was found that the best correlates of success in training were sample tests of job performance, gross dexterity, mechanical understanding, and reaction time. General ability, quantitative ability, and education were again found to be poor correlates of success (Hunter & Burke, 1995).

B. NAVAL AVIATION SELECTION TESTS

Predictors of success in flight training were developed during the Second World War. Large numbers of naval aviators were needed to meet the needs of the United States war effort, and a selection process for potential candidates was introduced. Subsequent revision and examination led to the formulation of the first naval aviation selection test, called the Aviation Selection Test Battery (ASTB) (Dean, 1996). This test, revised in 1953, and again in 1971, was composed of two parts: an Academic Qualification Test (AQT) and a Flight Aptitude Rating (FAR). The test was used as a measure to determine potential applicant success in flight training, using biographical data derived from a questionnaire that asked about family background, personal and medical history, environmental influences, education and vocational interests, in addition to academic skills.

The AQT portion was a general intelligence instrument designed to predict performance in the academic phase of training. The FAR was a composite score based upon individual scores of a Mechanical Comprehension Test (MCT), a Biographical Inventory (BI) and a Spatial Apperception Test (SAT). This composite score was intended to predict the probability of a student's success in the flight portion of training. In 1992, the test was again replaced in favor of a newer version.

The 1992 ASTB is the most recent revision in a series of cognitive tests used as a selection measure for potential naval aviators. This revision took place due to demographic changes, decreases in predictive validity of the previous test, possible AQT/FAR test compromise, and finally, due to changes in federal guidelines regarding employee selection procedures (Frank & Baisden, 1993). The new version of the ASTB consists of six sub-tests: 1) Math-Verbal Test (MVT), which tests general intelligence; 2) Mechanical Comprehension Test (MCT) which test the ability to perceive physical relationships and solve practical problems in mechanics; 3) Spatial Apperception Test (SAT), which tests the ability to perceive spatial relationships from different orientations; 4) Aviation and Nautical Test (AN), which tests for general aviation and nautical knowledge; 5) Biographical Inventory (BI) which is a questionnaire of personal history and interests; and 6) Aviation Interest (AI) which is a questionnaire of aviation-related items. Weighted combinations of the sub-tests result in three separate scores, each on a 9-point scale. These scores are used to predict attrition, academic performance, and basic flight performance of potential aviator candidates. The first score, called the Academic Qualification Rating (AQR), predicts flight school academic performance. The Flight Aptitude Rating (FAR) predicts basic flight performance while the Biographical Inventory (BI) predicts attrition.

The new version of the ASTB differs from the previous tests (utilizing AQT/FAR scores) in that only the BI is intended to predict attrition from primary flight training. Navy applicants must obtain qualifying scores of 3, 4 and 4 on the AQR, FAR, and BI for initial consideration into the flight program. Candidates receiving qualifying scores are further screened prior to acceptance into the training pipeline.

C. THE NAVAL FLIGHT TRAINING PROGRAM

Candidates selected for naval aviation training first attend a six-week course of ground school training at Aviation Preflight Indoctrination (API). During API, students master topics such as aerodynamics, aircraft engines, air navigation, meteorology, flight rules and regulations (FR&R), physical conditioning, and water survival, resulting in a total of 231 hours of instruction being received by each candidate. Upon completion of API, candidates are split into pilot and Naval Flight Officer (NFO) programs, and proceed to their respective training pipelines (Williams, Albert & Blower, 1999). Primary flight training introduces the student to actual flying experience, including basic instrument and radio instrument familiarization, close formation and night flying exercises. All flights are flown either in actual T-34C Turbo Mentor aircraft or the T-34C flight simulator. Student aviators are graded on preflight knowledge, emergency procedures, ability to think and react under stress, and other items related to the particular flight mission. Each student receives a grade between 1.0, which is considered "unsatisfactory," and 4.0, considered "above average," respectively. There are 530 graded items completed by each student aviator. A final score ranging from 1.0 to 4.0 is assigned, based upon the average of all scores received. After successful completion of primary flight training, each student then enters one of four aircraft pipelines for intermediate flight training. Selection to a particular pipeline is based on flight grades and the current needs of the Navy. In general, however, those with highest grades are selected for jets, followed by carrier-based propeller aircraft, maritime propeller aircraft and helicopters (Wahl, 1998).

Naval aviators are disqualified or dropped from the training pipeline for a variety of reasons. As stated above, many potential applicants are disqualified during the initial recruitment and selection phase; however, significant numbers drop out during the training process. A large cost is incurred when individuals drop from the training pipeline. As applicants progress through the training process, the cost for each applicant increases significantly. Reasons for withdrawal from training vary significantly, with categories including Drop on Request (DOR), Flight Failure, Not Physically Qualified (NPQ), Not Officer Material (NOM), Not Aeronautically Adaptable (NAA), Academic Failure and Other (misconduct, etc). Approximately 60% of all candidates fail due to medical disqualification. The Navy considers this amount to be unavoidable and not preventable. The goal for the Navy is to limit the number applicants withdrawing from training due to academic, flight failure, or DOR. Identification and early intervention by the Navy may result in subsequent cost savings to the training command and the Navy as a whole.

D. OFFICER PERFORMANCE MEASUREMENT

In 1976, ADM Hyman G. Rickover, Director of Naval Reactors, testified before the House Armed Services Committee that teaching Management as a major subject for an undergraduate did not contribute to the ability of a junior officer to do his job. He believed that all midshipmen should be taught electives limited to the technical sciences and that social sciences should be specifically excluded (Hearings on Military Posture, 1976). This belief led to the "Rickover Hypothesis," that the best naval officers are those who have a technical undergraduate major (Bowman, 1990). Bowman studied USNA graduates from 1976 through 1980 who entered the Surface and Submarine officer communities. He found that technical expertise diminished as officers advance to positions requiring greater managerial and administrative skills (Bowman, 1990). In addition, he found that retention factors are based upon personal characteristics, including perceived monetary options near the end of one's obligation, rather than academic background. Bowman's study applied only to USNA graduates, rather than the whole population of officers in the communities he studied.

Other studies that measure naval officer performance in a wide range of settings have been conducted. These examine topics ranging from specific aviator primary flight performance of USNA graduates (Reinhart, 1998), to Surface Warfare Officer (SWO) performance as related to commissioning source, undergraduate education and Navy training (Nolan, 1993). The following paragraphs highlight the research and results in areas related to officer productivity.

Reinhart (1998) utilized ASTB scores, along with other demographic variables, to compare primary flight training performance of 1995 and 1996 USNA graduates. He found that individuals who scored higher on the BI were more likely to complete primary flight training than those with lower scores. In addition, he found that those with higher AQR and FAR scores achieved higher grades than individuals with lower scores.

Foster (1990) measured the relative productivity of SWO and Submarine Officer (SO) officers from different accession sources, using a performance index derived from aspects of officer fitness reports, which allowed officers to be ranked or compared with one overall grade. Foster found that USNA graduates were rated higher, and that by a small margin, they were promoted earlier than graduates of other commissioning sources.

Nolan (1993) conducted a study of SWO promotion, retention and qualifications, as related to commissioning source, education and training. He used "Barron's Profile of American Colleges" to rank colleges according to their competitiveness. In addition, he utilized the Academic Profile Code (APC) that is assigned to each officer and which summarizes portions of an individual's undergraduate academic performance. The APC is broken down into three sections: grade point average (GPA); mathematics qualification code (MQC); and the technical qualification code (TQC). His results suggest that attendance at higher-rated colleges, having higher educational quality, was positively correlated to higher performance measures of effectiveness, such as promotion and early attainment of qualifications.

Woelper (1998) measured the impact of college grades, undergraduate major, college quality and commissioning source on SO job performance, as evidenced by early promotion and retention. His intent again was to test the "Rickover Hypothesis" that a strong technical background makes better naval officers. He found that engineering majors have higher completion rates through the training pipeline; however, major had an insignificant effect on junior officer performance or promotion to LCDR (Woelper, 1998).

E. BACKGROUND CONCLUSIONS

Aviator performance is difficult to measure. However, much work has been done to identify individual traits that point to successful completion of flight training. The civilian literature cited above (Puhlman & Fletcher, 1999) indicates that primary in importance is an individual's ability to master the mechanics and coordination required for flying. The ASTB enables the U. S. Navy to screen potential applicants, prior to committing limited funding and resources to individuals not suited for aviation. Further, Aviation Pre-flight Indoctrination attempts to identify as early as possible those individuals who are unable to complete the training regimen. Research conducted on the SO community seems to indicate that individuals with technical degrees are better than those with non-technical degrees, at least during training (Woelper, 1998). Work has been conducted that indicates that while academic background has a positive influence on officer performance at the initial training point, the lasting effect of undergraduate experience diminishes as time passes (Woelper, 1998). From the previous literature reviewed, it is expected that an aviator's academic background or college attended will influence flight school performance. In addition, higher ASTB scores will correlate with superior flight school performance, as evidenced by previous studies that have validated this test (Reinhart, 1998, Williams, Albert & Blower, 1999).

III. DATA AND METHODOLOGY

A. DATABASE DESCRIPTION

The first data set, provided by the Defense Manpower Data Center (DMDC), was derived from the Officer Master File (OMF), and contained both pre-commissioning and post-commissioning characteristics of naval officers. Data include demographic, educational background, billet assignment and promotion factors. The second data set contained information on flight school selection and performance by each individual. This data set was obtained from the Naval Aerospace Medical Research Laboratory (NAMRL) and contained 8,882 observations of students who were admitted for training at Naval Aviation Schools Command in Pensacola from 1988 through 1999. Included in this set were officers from other service branches and foreign countries. All non-USN naval aviators were removed from the data set, reducing the overall number to 6115 members. This file was then merged with the OMF file, resulting in 5123 matches in the combined data set. The resulting aviator subset of data was further reduced in size to 3937 observations due to missing observations of other key variables, including undergraduate major, aviation pipeline, flight school performance scores and university attended. This data set was further divided by removing the NFO's from consideration, leaving 2612 student aviators. Once the final data set was completed, variables were created or factors modified to better isolate characteristics of interest to this study. A breakdown of the final data set column descriptions can be found in Appendix A.

B. KEY INDEPENDENT VARIABLE DESCRIPTION

Several key variables were created from the above data sets. The first variable derived was "MAJOR," which separated college degrees awarded into three categories.

These categories were obtained from the Office of the Chief of Naval Operations (CNO) which listed "Non-Technical," "Technical" and "Math-Science Technical" majors as possible courses of study for the future naval officer (CNO, 1999). Non-technical majors such as history and accounting were assigned to the first factor level, while non-engineering technical majors such as math and physics were assigned to the second level. Engineers were assigned to the third factor level. As indicated above, if information about the college degree awarded to an individual was absent from the data set, then the individual was removed from consideration.

The second key variable is "COLLEGE," which was created using a combined listing of collegiate rankings as provided by U.S. News and World Report (Elfin, 1990; 1995). Colleges were rated according to six attributes – reputation, selectivity, faculty resources and financial resources, retention and alumni satisfaction. The schools were divided into "National" and "Liberal Arts" colleges. They were then ranked according to the attributes listed above. The top quartile schools by rank were included for the purposes of this study. In order to do this, the top schools from both 1990 and 1995 were merged to provide coverage for aviators who otherwise might not have been included. Each individual was coded as having attended either "none," "national" or "liberal" to signify the school rank they attended. After final review, the factor levels for "liberal" and "national" were combined because only a few individuals attended top ranked liberal arts colleges included in the data set. None of the service academies were included in the final rankings by U.S. News & World Report even though a significant percentage of individuals attended the Naval Academy. These individuals were placed within their own factor level.

"Academic Profile code" (APC) is another key variable from which three sub-categories were obtained. The APC code is a three-digit code that summarizes pertinent portions of an Officer's prior college performance. The first digit indicates overall academic performance. The second represents mathematical background and the third represent course coverage in science and technical fields. The three separate digits reflect an individual's cumulative grade point average, exposure to and performance in calculus-related mathematics and selected science/engineering areas. Use of the APC is limited in that only about 40% of the pilots in the data set have been assigned this code. The individual digits of the APC code were re-classified into a binary variable based upon individual performance. A binary code of 1 was assigned to individuals who demonstrated B+ or better GPA, math and/or technical backgrounds.

Other variables were derived from the data set for ease in manipulation. "RACE" and "ETHNIC" categorical variables were coded according to major divisions. Initially, they consisted of numerous factors, some of which contained only a few individuals. "RACE" was reduced to factors of "White," "Black," and "Other". "ETHNIC" was coded to allow "None," "Hisp," "Asian" and "Other" as possible factor levels. Commissioning Source was also used, with factor levels of "OCS," "NROTC," and "USNA" being created for the categorical variable "SOURCE." Finally, both "FAR" and "AQT" integer variables were used from results of the ASTB scores.

C. KEY DEPENDENT VARIABLE DESCRIPTION

Aviator's flight school completion status was determined by "CURRSTAT," which identified whether or not an individual completed or withdrew from flight school. This categorical variable allows model formulation using either classification trees or by Logit regression due to its binary nature.

Another measure of effectiveness was the composite score obtained from attendance at the initial flight training school attended. This score, from the Navy Aviation Schools Command (NASC), is based upon a student's performance in API and measures academic performance in the early stages of the aviation-training pipeline. This explanatory variable was called "NASCNSS" and is continuous in nature.

Two other continuous variables were used. The first, "PASS," reflected the standardized academic score achieved during Primary flight training, while "PFSS" was a measure of flight performance during the same period.

D. METHODOLOGY

Statistical analysis starts by using Classification and Regression Trees (CART) to model performance of individuals in the aviator-training program. Trees have the advantage that they are easier to interpret when the predictors are a mixture of categorical levels and numeric entries. Furthermore, the response can either be a continuous or a categorical value. Thus CART can be used for either "CURRSTAT," which is a categorical response, or for the other response variables, which are continuous.

A tree is formed by measuring the amount of variation or deviance between each predictor and the response variable. The predictor that reduces variation or deviance by the greatest amount becomes a "parent" node and a partition is made, dividing the parent node into two "child" nodes that contain all the other predictor variables. Each child node then becomes a parent and the process repeats itself. This process continues until there are no members of a factor left to split or if a preset minimum deviance reduction level is reached.

The process is binary because parent nodes are always split into exactly two child nodes and recursive because the process can be repeated by treating each child node as a parent. (Breiman, et. al., 1984).

After the initial tree model is determined, cross-validation (CV) is used to optimize the predictive reliability of the tree model. Several methods of cross-validation exist; however this thesis utilizes *V*-fold cross-validation (Statsoft, 2000). This type of cross-validation is useful when no test sample is available and the learning sample is too small to have the test sample taken from it. A specified V value for *V*-fold cross-validation determines the number of random sub-samples, as equal in size as possible, that are formed from the learning sample. The classification tree is computed V times, each time leaving out one of the sub-samples from the computations, and using that sub-sample as a test set, so that each sub-sample is used $V-1$ times in the learning sample and just once as the test sample.

Finally, the total amount of deviance reduction is measured as each node of the crass-validated tree is generated. As the tree increases in size and complexity, an optimal point will be reached. At this point, the most important splits in the tree have been determined. The tree is then pruned so that only these factors are used in final tree construction. The resultant tree provides the user a tool for making predictions about individuals contained in the data set. Further, the tree has effectively screened and identified the most useful predictor variables from the data. These variables provide the initial inputs to the Logistic and Least-Squares regression models subsequently formulated. Since the focus of this study is to determine the impact on academic major and quality of college attended, "COLLEGE" and "MAJOR" are added to the Logistic and Least-Squares models along with the predictors identified by CART, if not already identified by the tree created.

The Logistic model uses the predictor variables identified by the CART model, along with the academic background variables to get an estimated "Logit" for individuals in the data set. This value is analogous to the estimator $\hat{Y}$ that is calculated using Least-Squares regression. A full model is developed, and then a step function is applied to reduce this model, keeping only those predictors that provide the most information in the model. This step function uses the Akaike Information Criterion (AIC), and measures the model effectiveness, based upon sample size and the number of predictors in the model. If a predictor does not provide statistically significant information based on the AIC, it is not included in the final model formulation (Agresti, 1990). The final Logistic model can be formulated as:

$$L_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_{k-1} X_{i,k-1}$$

Using an inverse transformation, a predicted probability of flight school success for the individual can be calculated. Thus,

$$\hat{P} = \frac{1}{1 + e^{-L}}$$

Using this transformation, the predicted success probability for each member of the data set can be computed, based upon his or her educational and demographic background and flight school performance data (Hamilton, 1992).

IV. RESULTS

A. DATA ANALYSIS

The student aviator data set contains 2612 members, of which 150 are women. Of these members, 2144 completed training, while 468 failed to complete the pipeline. The data set examined did not provide an explanation for early departure from the flight-training program. There were 1235 NROTC graduates, 991 USNA graduates, and 386 OCS graduates in the program. A complete breakdown of these and all other elements of the student aviator data set can be found in Appendix B.

A two-way contingency table was arranged and a chi-square test of independence was conducted, with a null hypothesis was that there were no differences between majors based upon the proportions that completed the flight-training program. The null hypothesis was rejected, indicating that there is a difference between majors (chi-square = 29.9662, df = 2, p-value = 0). Comparisons were made to determine how the majors differed from each other. No significant differences between non-technical and technical majors were found (chi-square = 1.0226, df = 1, p-value = 0.3119). However, between non-technical majors and engineers, significant differences exist (chi-square = 29.3487, df = 1, p-value = 0). Technical majors and engineers were compared, with significant differences found (chi-square = 6.3579, df = 1, p-value = 0.0117). Finally, technical majors and engineers were combined, and then compared to non-technical majors, resulting in significant differences being detected (chi-square = 23.8068, df = 1, p-value = 0). In summary, non-technical majors have significantly lower completion rates than the combined set of technical and engineering counterparts (Table 1).

	Non-Technical Majors	Technical Majors	Engineering Majors	Technical and Engineers	Total
Completed	1036	247	861	1108	2144
Attrited	285	57	126	183	468
Total	1321	304	987	1291	2612
Proportion Completing Training	78.43%	81.25%	87.23%	85.82%	82.08%

Table 1. Student aviator completion rate, based upon Undergraduate Major. There is no evidence that differences exist between non-technical and technical majors, but do exist with engineering majors, and between non-technical majors when compared against both technical majors and engineers combined.

A CART was formed using the "CURRSTAT" dependent variable, indicating completion/attrition status. The model is as follows:

CURRSTAT ~ SEX + AQT + FAR + RACE + MAJOR + ETHNIC + SOURCE + COLLEGE + GPA + MATH + PHYSICS

A full, saturated tree was generated and cross-validated using V-fold CV with ten holdout sets. Figure 1 displays the deviance plot of the cross-validated tree.

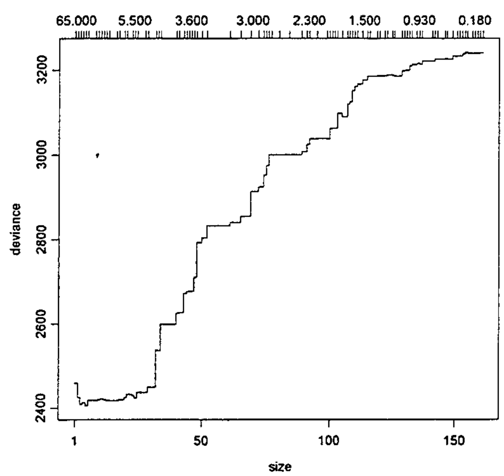

Figure 1. Size vs. deviance plot for CURRSTAT model.

The minimal point of the deviance plot is five, indicating that a tree with five terminal nodes provides the most accurate prediction. The tree was pruned to reflect this optimal level. All variables were made available to the algorithm; Figure 2 shows that only FAR, AQT and RACE were actually chosen. (For more details on the construction of trees see Breiman *et al.*, 1984.) Results indicate that the best predictors consist of FAR, AQT and RACE (Figure 2). In this and other tree pictures, ovals represent non-terminal nodes and rectangles, terminal ones. Each node is labeled with the proportion or average in that node – in this case, the proportion of aviators undergoing attrition. Beneath each node the number of aviators falling into that node is given.

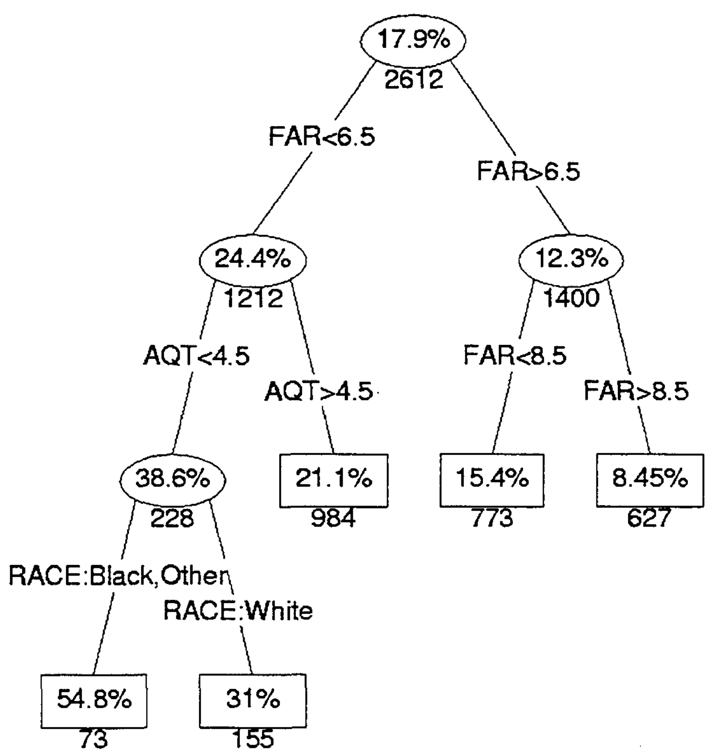

Figure 2. Reduced Aviator CURRSTAT Tree, with FAR, AQT and RACE as significant predictors of completion and attrition.

The above figure indicates that those individuals who score six or less on the FAR have a 24.4% attrition rate, while those who score 7 or above have a 12.3% attrition rate. Further, individuals who have a score or 4 or less, given that they have scored a 6 or less on the FAR have a 38.6% attrition rate. Finally, those individuals who are "Black" or "Other" in the RACE category are predicted to have a 54.8% attrition rate, given that they have a score of 6 or less on the FAR and a 4 or less on the AQT. The tree model indicates that the Navy should focus efforts to recruit individuals with higher FAR and AQT scores.

After CART optimal tree determination, a Logit model was formed using FAR, AQT, and RACE, along with MAJOR and COLLEGE. A full model was created using single predictors and their two-level interactions. Following creation of this model, a step function using the AIC was utilized to determine the optimal reduced model. Final model formulation is:

$$L_i = \beta_0 + \beta_1 FAR + \beta_2 AQT + \beta_3 RACEOther + \beta_4 RACEWhite + \beta_5 MAJOR1 + \beta_6 MAJOR2$$
$$+ \beta_7 COLLEGE1 + \beta_8 COLLEGE2 + B_9 FAR:AQT + \beta_{10} FAR:COLLEGE1 + \beta_{11} FAR:COLLEGE2$$

Results from the Logistic regression model indicate that engineering majors perform significantly better than individuals who hold non-technical degrees (MAJOR2 ($t(2600)= 3.39$, $p < 0.001$). Individuals who attended the Naval Academy also performed better than those who attended non-ranked civilian institutions (COLLEGE2 ($t(2600) = 2.75$, $p < 0.01$). In addition, FAR ($t(2600) = 5.51$, $p < 0.001$), AQT ($t(2600) = 2.48$, $p < 0.01$) and RACEWhite ($t(2600) = 4.03$, $p < 0.001$) are significant. In this model, "White" individuals perform significantly better than their "Black" counterparts. In addition to the single variable predictors above, a significant negative interaction was observed between FAR and AQT ($t(2600) = -3.14$, $p < 0.01$). Finally, an interesting interaction was observed between individuals who attended the Naval Academy and how they performed on the FAR. Results indicate that each point increase on the FAR decreases the log-odds by 0.165 (t(2600) = -2.25, $p < 0.05$). Reasons for this are unclear. Table 2 gives a listing of the above independent variables, their coefficient estimates B_i, their resulting t-statistics and finally, their level of significance.

	LOGIT	Std. Error	t value	Significance
(Intercept)	-3.8352	0.8478	-4.52	NS
FAR	0.7527	0.1366	5.51	***
AQT	0.3862	0.1557	2.48	**
RACEOther	0.1256	0.2807	0.48	NS
RACEWhite	0.8482	0.2107	4.03	***
MAJOR1	0.1259	0.1696	0.74	NS
MAJOR2	0.4223	0.1246	3.39	***
COLLEGE1	-0.5809	0.6003	-0.97	NS
COLLEGE2	1.2965	0.4712	2.75	**
FAR:AQT	-0.0710	0.0226	-3.14	***
FARCOLLEGE1	0.0753	0.0888	0.848	NS
FARCOLLEGE2	0.1651	0.0735	-2.25	*

*** Significant at the alpha = 0.001 level

** Significant at the alpha = 0.01 level

* Significant at the alpha = 0.05 level

NS Not Significant

Table 2. Logit regression results for Aviator CURRSTAT model.

The results of the Logit model can be used by the Naval Recruiting Command to set quotas for student naval aviator billets. Each year, the Chief of Naval Operations Aviation Air Warfare identifies the number of student aviator billets required to maintain aviation military readiness in the future. There are fewer billets available due to the military budget reduction, thus manpower analysts must maintain high retention rates for each aviation year group or there will be aviator shortages several years later. An aviation manpower analyst can use this Logit model to predict whether or not an individual will successfully complete flight school training. By selecting individuals who have a higher probability of completing flight school, the Navy may not experience the current retention problems that has plagued the aviation community these past few years. For example, suppose a recent white USNA graduate with an engineering degree scored a six on both the FAR and on the AQT. Using these characteristics, a resulting Logit for this individual can be calculated using the model formulation below:

$$
\begin{aligned}
L_i &= \beta_0 + \beta_1 FAR + \beta_2 AQT + \beta_3 RACEOther + \beta_4 RACEWhite + \beta_5 MAJOR1 + \beta_6 MAJOR2 \\
&+ \beta_7 COLLEGE1 + \beta_8 COLLEGE2 + \beta_9 FAR:AQT + \beta_{10} FAR:COLLEGE1 + \beta_{11} FAR:COLLEGE2
\end{aligned}
$$

$$
\begin{aligned}
L &= -3.8352 + 0.7527*6 + 0.3862*6 + 0.1256*0 + 0.8482*1 + 0.1259*0 + 0.4223*1 \\
&+ (-0.5809)*0 + 1.2965*1 + (-0.0710)*6*6 + 0.07530*0 + (-0.1651)*6 \\
&= 2.0186
\end{aligned}
$$

Performing the inverse transformation:

$$\hat{P} = \frac{1}{1+e^{-L}} = \frac{1}{1+e^{-2.0186}} = 0.883$$

From this, it is predicted that this individual would have a success probability of 88%. On the other hand, if a recent black student who graduated from a non-ranked institution with a non-technical degree had scored a 4 on the AQT and a 5 on the FAR was considered. Calculating the appropriate Logit:

$$L_i = \beta_0 + \beta_1 FAR + \beta_2 AQT + \beta_3 RACEOther + \beta_4 RACEWhite + \beta_5 MAJOR1 + \beta_6 MAJOR2$$
$$+ \beta_7 COLLEGE1 + \beta_8 COLLEGE2 + \beta_9 FAR : AQT + \beta_{10} FAR : COLLEGE1 + \beta_{11} FAR : COLLEGE2$$

$$L = -3.8352 + 0.7527 * 5 + 0.3862 * 4 + 0.1256 * 0 + 0.8482 * 0 + 0.1259 * 0 + 0.4223 * 0$$
$$+ (-0.5809) * 0 + 1.2965 * 0 + (-0.0710) * 5 * 4 + 0.07530 * 0 + (-0.1651) * 0$$
$$= 0.5310$$

Performing the inverse transformation:

$$\hat{P} = \frac{1}{1+e^{-L}} = \frac{1}{1+e^{0.5310}} = 0.6297$$

This individual's predicted success is 63%.

The next analysis of the student aviator data dealt with the results of the pilots who ultimately completed training on their first composite grade from aviation flight school. Model formulation was the same as above, but this time using the standardized score, NASCSSC, as the dependent variable. Model formulation is:

NASCSSC ~ SEX + AQT + FAR + RACE + MAJOR + ETHNIC + SOURCE + COLLEGE + GPA + MATH + PHYSICS

This score is the first that student aviators receive upon admittance into the flight-training program. It represents a time when they are most competitive, and are striving to perform at their peak in order to have the best pipeline selection choice. Results for deviance reduction are similar to the findings above, with an optimal tree of three terminal nodes created. Most important are FAR and AQT. This result is not surprising, since the purpose of the AQT and the FAR is to predict performance in flight school during the API and primary phases. Individuals who score seven or less on the FAR are predicted to have a NASCNSS score of 51.49%, while individuals who score above seven are predicted to have a score of 54.53%. Further, individuals who score five or less on the AQT, given that they have scored a seven or less on the FAR are predicted to have a score of 49.88%. The trend indicates that higher FAR and AQT scores lead to higher composite scores achieved during API. Figure 3 shows the reduced tree model.

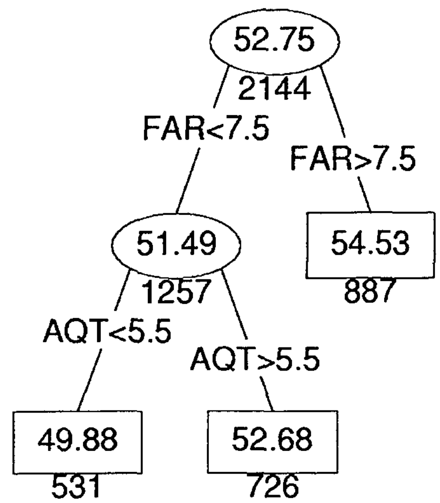

Figure 3. Reduced NASCNSS tree model.
Indicates that only FAR and AQT are significant
predictors of API performance.

A plot of the normalized distribution of the residuals was made for the NASCNSS data. Results (Figure 4) indicate highly skewed tails on both ends of the data set. A review of the original data indicated that some individuals had very low scores, yet had completed the training pipeline. Similarly, some individuals had high composite scores, while their raw score was lower. This may be indicative of poor data collection and entry efforts and adversely impacts the significance of this finding.

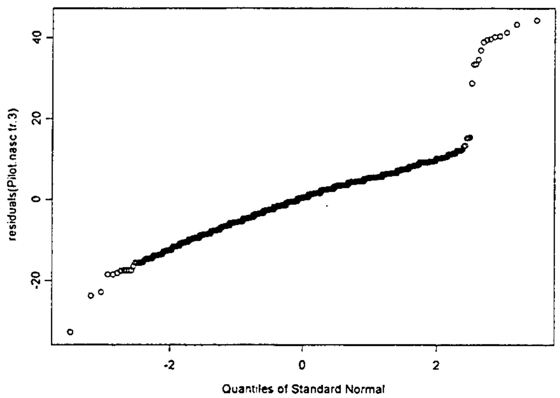

Figure 4. Standard normal plot of quantiles vs. residuals for the NASCNSS Model.

Least-Squares regression on the NASCNSS model was conducted. A step function was utilized to determine the optimal linear model, using the AIC. The final model included FAR, AQT, MAJOR and COLLEGE, with a significant interaction between FAR and AQT. Both FAR ($t(2136) = 4.87$) and AQT ($t(2136) = 4.66$) are significant with resultant p-values = 0.00. Technical degreed aviators ($t(2136) = 2.08$, $p < 0.05$) and engineers ($t(2136) = 2.53$, $p < 0.05$) were also significant. Of note is that there is no significant effect from individuals that attended the USNA as compared to the baseline group. However, individuals who attended top ranked institutions performed significantly better than those who attended non-ranked universities ($t(2136) = 3.04$, $p < 0.005$). Finally, a high degree of correlation was evident between FAR and AQT (0.9143), leading to a significant interaction between these two terms ($t(2136) = -2.93$, $p < 0.005$). A possible explanation for this result is that some individuals might score high on one predictor but low on the other; however, this is not entirely clear from the analysis. The total variation explained by the model was only 12%, indicating that the model does not fit very well. A summary of the data output is displayed in table 3.

	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	35.750	2.574	13.887	0.000
FAR	1.740	0.357	4.870	0.000
AQT	2.075	0.445	4.662	0.000
MAJOR1	0.458	0.221	2.076	0.038
MAJOR2	0.261	0.103	2.534	0.011
COLLEGE1	0.546	0.180	3.036	0.002
COLLEGE2	0.693	0.097	0.715	0.475
FAR:AQT	-0.175	0.060	-2.932	0.003

Table 3. Least-Squares regression results for aviator NASCNSS model.

All pilots, after completion of API, transition to primary flight training. In primary, the real education of a pilot begins. Students are introduced to the flight trainer and actually spend time in the cockpit learning to develop flying skills. In addition, academic work continues, and students receive a composite score for each part during this phase of the training program. The ASTB is designed to use AQT to predict academic performance, while the FAR is supposed to predict performance in the flight school portion of primary. Of interest is whether or not these characteristics hold true, and see if there are other significant predictors using CART. The academic model formulation is:

PASS ~ SEX + AQT + FAR + RACE + MAJOR + ETHNIC + SOURCE + COLLEGE + GPA + MATH + PHYSICS

Analysis followed the same methodology as above, and an optimal minimal spanning tree with nine terminal nodes was developed. Results indicate that individuals who score six or lower and are not "White" score the lowest, with a predicted score of 43.55%. On the other hand, "White" individuals who score below a seven on the FAR have scores ranging from 48.28% to 57.03% based on their AQT score. Lower AQT scores are indicative of lower scores during the academic portion of Primary. For individuals that score a seven or above on the FAR and have a technical or an engineering degree, they are predicted to score a 55.42% during this training phase. Further, if they score eight or higher on the AQT, they are predicted to finish with a 57.26% final score. Close examination of the tree model indicates that lower FAR and AQT scores result in lower predicted composite scores achieved during the academic portion of primary (Figure 5). Finally, using the normalized QQ plot to inspect the distribution of residuals, it is apparent that there is one point that requires further investigation (Figure 6). A review of the data set indicated that this individual had the highest standardized score, while his raw score was lower than that of many of his peers. It is believed that this is another case where faulty data entry is causing the discrepancy.

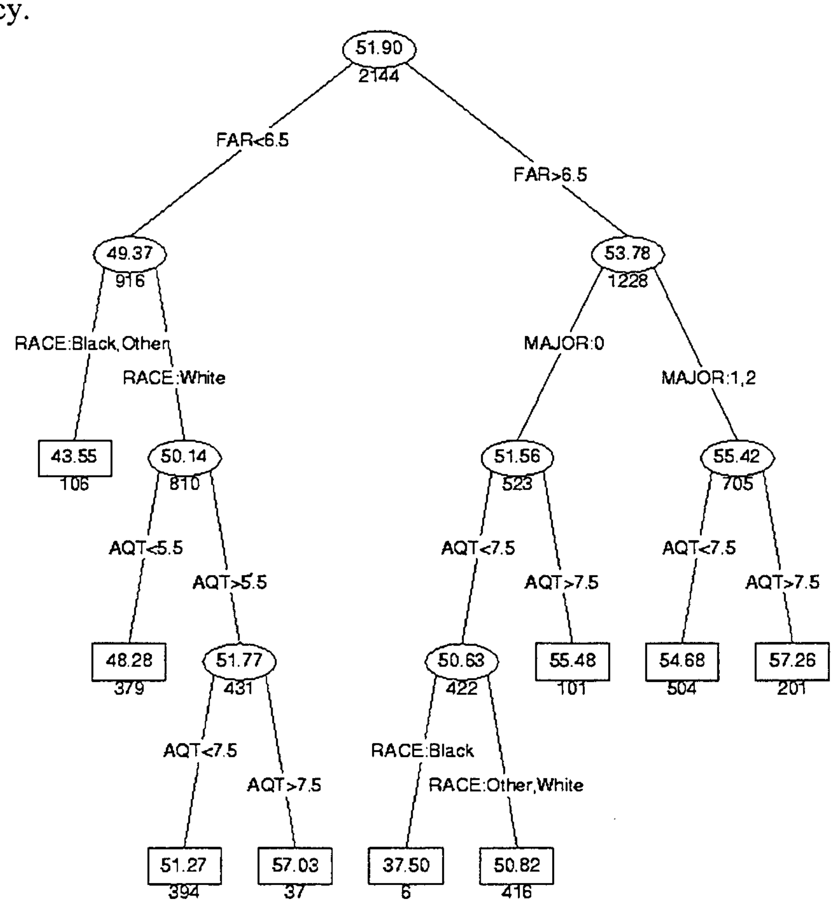

Figure 5. Reduced PASS tree model. Results indicate that FAR, RACE, MAJOR, and AQT are significant factors in tree construction.

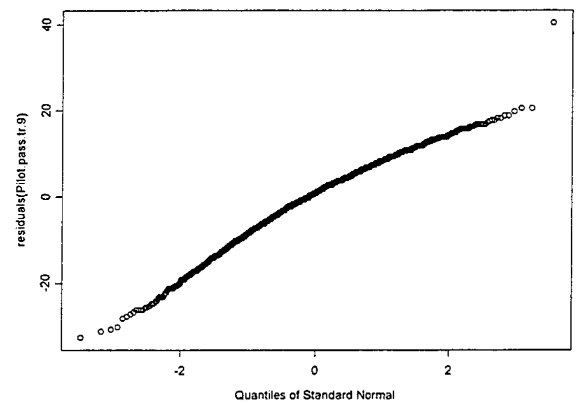

Figure 6. Standard normal plot of quantiles vs. residuals for the PASS model.

A Least Squares regression model was again formulated using the techniques described above with the results shown in table 4 below. Independent variables used in model selection include FAR, MAJOR, AQT, RACE and COLLEGE. Notice that all factors are significant at the alpha = 0.05 level or better in this model. However, the total variation explained by the model was only 8%, indicating that while statistically significant, there is question about the usefulness of this result.

	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	30.8379	1.2957	23.7997	0
FAR	0.9016	0.1254	7.1904	0
MAJOR1	1.8064	0.6129	2.9474	0.0032
MAJOR2	2.6708	0.4101	6.513	0
RACEOther	2.7437	1.3982	1.9624	0.0498
RACEWhite	6.2315	1.056	5.901	0
AQT	1.1012	0.1557	7.0736	0
COLLEGE1	1.4543	0.4989	2.9149	0.0036
COLLEGE2	1.4562	0.4397	3.3115	0.0009

Table 4. Least-Squares regression results for aviator PASS model.

The final analysis was conducted, similar to the methods above, on the PFSS dependent variable. FAR is expected to be a significant predictor of these scores, based upon the validity of the ASTB. Model formulation is:

PFSS ~ SEX + AQT + FAR + RACE + MAJOR + ETHNIC + SOURCE + COLLEGE + GPA + MATH + PHYSICS

Again, there is significant deviance reduction, with an optimal tree of nine nodes. A tree grown using this value resulted in FAR , RACE, COLLEGE, MAJOR, and ETHNIC being the important factors in this model. Individuals who score six or less on the FAR and are not "White" are predicted to score lowest among all groups. Non-technical majors who attend non-ranked colleges also fare poorly, if they score a seven on the FAR, as compared to their technical and engineering counterparts who fall within the same category. The minimal spanning tree plot is displayed below (Figure 7) along with the normalized QQ plot (Figure 8).

A Least Squares regression analysis was conducted on the PFSS data using predictors FAR, AQT, MAJOR, ETHNIC and COLLEGE. Use of the step model removed AQT from consideration. Results indicate that FAR was highly significant ($t(2129) = 15.62$, $p = 0.00$) while MAJOR did not have an effect on performance during PFSS. There was a significant effect of the RACE predictor, with "White" ($t(2129) = 4.44$, p 0 0.00) and "Other" ($t(2129) = 2.55$, $p < 0.01$) categories performing significantly better than "Blacks." In addition, the USNA graduates fare better than their non-ranked school counterparts at the alpha = 0.10 level. Significant interactions were present. Individuals who attended the USNA that held technical or engineering degrees performed better than their non-technical counterparts. Finally, it is important to note that these predictors explained only 16% of

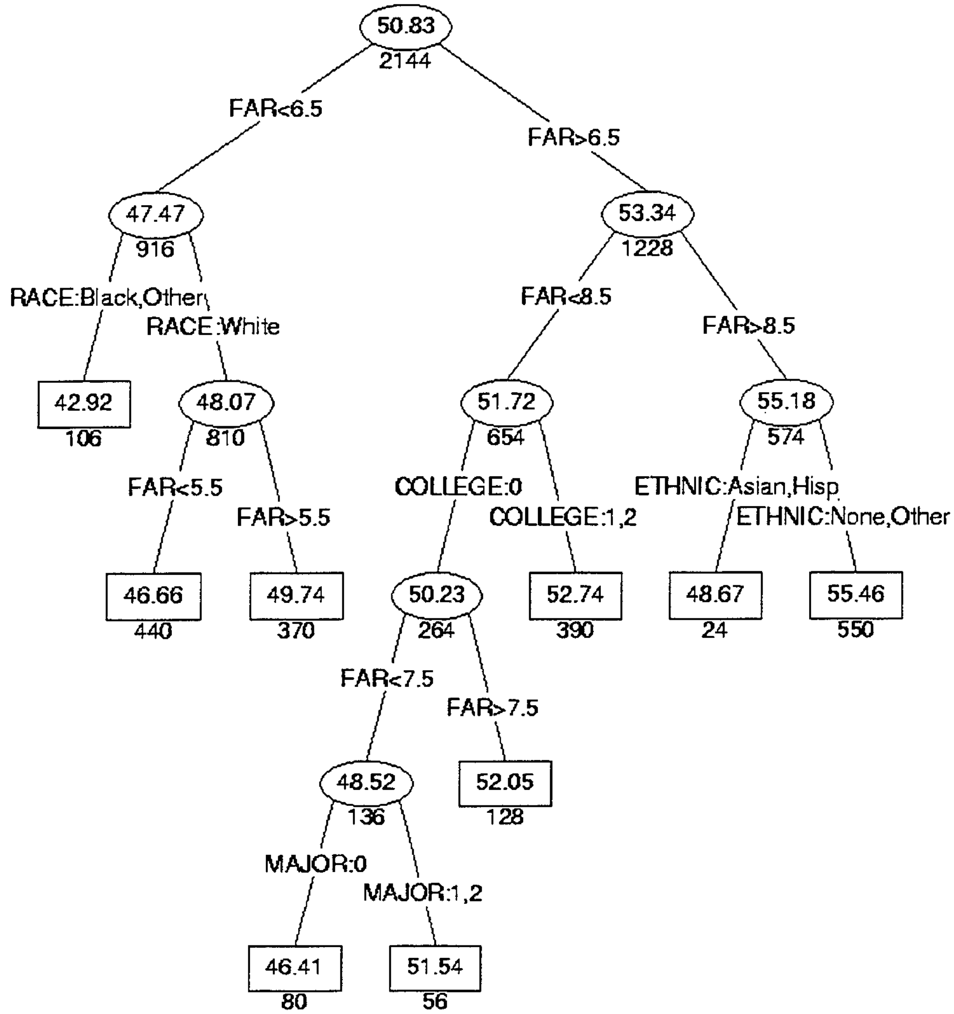

Figure 7. Reduced PFSS tree model. Results indicate that FAR, RACE, MAJOR, and AQT are significant factors in tree construction.

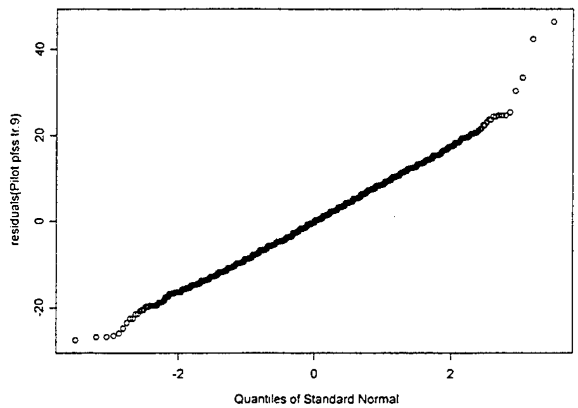

Figure 8. Standard normal plot of quantiles vs. residual for PFSS model. Some outliers are present, as indicated by the skewed plot tails.

the total variation in the data set as evidenced by the value of R^2 that was calculated for this regression model. Table 5 displays the output for this model.

	Value	Std. Error	t value	Pr(> |t|)
(Intercept)	28.6916	2.2066	13.0025	0
FAR	1.8821	0.1205	15.6162	0
MAJOR1	-0.5652	1.0826	-0.5221	0.6017
MAJOR2	0.7012	0.6531	1.0737	0.2831
RACEOther	4.3549	1.7067	2.5517	0.0108
RACEWhite	4.7542	1.0705	4.441	0
COLLEGE1	0.8577	0.6979	1.2289	0.2192
COLLEGE2	1.2226	0.6749	1.8114	0.0702
ETHNICHisp	-0.1234	1.8008	-0.0685	0.9454
ETHNICNone	3.9332	1.8427	2.1345	0.0329
ETHNICOther	2.6099	1.8536	1.408	0.1593
MAJOR1COLLEGE1	2.3856	1.9485	1.2243	0.221
MAJOR2COLLEGE1	-1.0833	1.0511	-1.0306	0.3028
MAJOR1COLLEGE2	2.4013	1.3951	1.7212	0.0854
MAJOR2COLLEGE2	1.6045	0.9298	1.7256	0.0846

Table 5. Least-Squares regression results for aviator PFSS model.

V. DISCUSSION

A. SUMMARY

The present policy of the Aviator Recruiting Command is to recruit those individuals most likely to succeed in the flight-training program, based upon their ASTB scores and physical attributes. In addition, emphasis is placed on recruiting individuals having "technical" undergraduate majors. This follows the "Rickover Hypothesis," that individuals with technical degrees make better officers than their non-technically educated counterparts. The recruiting focus is supposed to be placed on individuals with technical degrees; however, it is apparent that this precept is not followed because of the nearly equal proportions of aviators with non-technical majors and those with technical or engineering majors combined. This distribution provides the ability to make a direct comparison between the performances of each group. The evidence indicates that aviators with engineering degrees have a greater propensity for completing the training pipeline than their technical and non-technical counterparts. This echoes the conclusion found by Woelper (1998), who determined that SO's with engineering degrees had higher completion rates than their non-engineering counterparts in the nuclear power training process. However, he also indicated that no effect on performance was observed after completion of training, indicating that the effect of undergraduate major diminishes as one progresses upward in his or her Naval Career (Woelper, 1998).

Many factors affect pilot performance during the training process; however, they are numerous and not well defined. Initial review of the above results seems to indicate that MAJOR and COLLEGE are significant factors in pilot development; however, this conclusion must be viewed with caution. Although the explanatory variables for each performance measure were statistically significant, one must ask whether or not these variables account for all the variation observed by the model formulation. Because residual deviance was very high in the CART models, and the corresponding R^2 value was extremely low in all of the least squares regression models, inferences about this result are difficult to make. However, certain observations can be made.

The first observation to consider is MAJOR. The data suggest that individuals with engineering degrees perform better during API and in the academic portion of Primary flight training, as indicated by significant findings in these areas. On the other hand, the effect of holding a "technical" degree was not significant during the flight portion of Primary. This indicates that while a strong educational background in a technical field increases the likelihood of having higher academic grades and less likelihood of withdrawal from the flight-training program, there is little relationship between this degree and flight school performance in the air.

The second observation deals with the importance of COLLEGE. In all but the NASCNSS model, USNA attendance was an important predictor of success, whether dealing with completion rates, or when comparing grades. It can be hypothesized that individuals who attended the Naval Academy have better preparation than their NROTC and OCS counterparts due to the unique experience they receive through attendance and participation in the military institution. In short, they perform better because they are more disciplined and require less time to acclimate to the military surroundings than their counterparts, resulting in greater attention to the primary task at hand. It is important to note that SOURCE was not a factor named in any of the CART models, indicating that there is not much difference when approached from this angle. However, evidence suggests that individuals who attend top-ranked institutions and those who attend the USNA fare better than their counterparts, regardless of whether or not they entered through OCS or NROTC.

Finally, both the AQT and FAR measures were identified in the CART models, leading to the belief that they are performing their job as predictors of success in the aviation program. The results of this study seem to further validate these measures of performance and suggest that the ASTB be retained as an initial screening tool for aviators.

Several issues and problems with the above conclusions need to be discussed. First is the issue of data accuracy and completeness. In many instances, large blocks of the data set had to be excluded due to missing data or other inaccuracies in the data files. For instance, 795 members of the NAMRL data set were unable to be matched by social security number in the OMF data files, even though they were listed as being naval officers. Numerous other instances occurred where individuals were listed as completing the flight-training pipeline, but did not have NASCNSS, PFSS, or PASS grades entered. Another problem was that some individuals were listed as having attended the USNA, as identified by COLLEGE, yet these same individuals were listed as having commissioning source of OCS or NROTC. All of these individuals were removed from consideration during analysis.

Another important issue is the question of sample size. In statistical analysis, a large sample size enables one to detect even small differences between measures of performance, based on explanatory variables. However, judgment must be made to determine if statistically significant results are of practical use. These results must be viewed with this in mind. A population of 2612 pilots provides ample room to find even minute differences between groups of people. Further, the population from which the results were derived must be representative of the set of all aviators who attended flight school. In conclusion, it is believed that differences do exist between pilots, based upon their academic background. However, the practical necessity of recruiting pilots who meet the minimum standards to maintain required manning levels requires focus on those that might not have attributes that are strong predictors of success as determined from this analysis.

A third issue deals with the absence of data reflecting actual performance of an individual during his or her undergraduate education. The APC is supposed to provide information regarding overall academic performance, in addition to performance in mathematics and physics. Only 40% of the individuals in the data set held the APC. The APC is computed by the Naval Postgraduate School (NPS), usually within three years from commissioning. However, individuals must ensure that college transcripts are forwarded to the school for computation. This score is required for acceptance into NPS and for consideration of acceptance into other graduate school programs. An individual who does not desire to pursue a graduate education might not request that their transcripts be forwarded. It is possible that a significant number of individuals who lack this code might have lower grades, and therefore consider themselves ineligible for graduate education. The APC and its sub-scores of GPA, MATH and PHYSICS were not utilized in final model formulation; however, with a more complete data set, this information could have been used to develop a more accurate picture of flight school performance.

Most important, however, is the issue of the determination of completion and attrition. The data sets provided did not provide reasons for attrition, necessitating all those who withdraw be included in the model. Identification of those who attrite for medical reasons, or reasons not related to individual performance, would hopefully provide more useful data for analysis. This would limit the analysis to that of those individuals who had difficulty in performing academic or flight-related tasks and enable a more precise identification of factors related to successful flight school completion. Nevertheless, the models do indicate a relationship between AQT and FAR and flight school performance, indicating that these measures are performing as designed. The factors of MAJOR, COLLEGE, and RACE also provide predictive power. Even without knowing the cause of attrition, inferences can be made on an individual's performance, based upon the factors listed above. This model does not attempt to predict attrition, however. It merely identifies factors that indicate successful flight school completion and, using the CART methodology, classifies individuals into groups with common characteristics.

B. RECOMMENDATIONS

The present recruiting policy for naval aviators is to place emphasis on recruiting individuals with technical degrees. This policy is sound, given the above results. There are limitations to this, as indicated by the number of aviators with non-technical degrees who are already in the fleet. It is impossible, in today's difficult recruiting environment, to find only those individuals who have engineering degrees and otherwise meet all entrance specifications. The CART and Logit models should be utilized to compare traits of individuals, recognizing that each of the significant factors in this model is associated with the individual's predicted success likelihood. Those individuals who have characteristics associated with higher success probability or to higher predicted composite scores should be recruited, if possible. Focus should be given to those individuals who are predicted to perform the best in the training program, as described below.

There are several factors that seem to provide consistent improvements throughout this analysis. These include AQT, FAR, RACE, MAJOR and COLLEGE. Higher ASTB scores, which predict success likelihood in both the academic and the flight school portions of the training pipeline, result in higher predicted completion rates and higher composite scores. Individuals who have technical degrees, or who attend the Naval Academy also fare better than their counterparts. Neither of these results is surprising. Individuals who are White have higher completion rates, and higher composite scores, too. This result was unanticipated and the reasons for these differences are not clear. Perhaps it reflects the contribution of other, unmeasured attributes of the aviators; possibly it reflects cultural biases in the tests themselves. This thesis does not recommend against selection of racial minorities; however it does suggest that the selection process can take into account an individual's background and use the Logit or CART model to estimate success probability. Students with low estimated probabilities are natural targets for intervention strategies designed to improve retention and thereby preserve the Navy's investment.

There are some areas that need to be analyzed further. First, this study only looks at pilots, and not at Naval Flight Officers. However, during the analysis, some statistical work was done relating to this group of individuals in which results similar to those found above were obtained. A more detailed analysis should be conducted before conclusions about the NFO community are reached.

Second, greater emphasis needs to be placed to ensure accuracy and completeness of data entry. All statistical analysis can only be as good as the data it models. It is therefore recommended that the data collection process be reviewed and improvements made in order to improve the process of statistical analysis.

Individual pilots maintain training folders; however, these folders are kept locally at each command and are not compiled into a central database. There is no methodology for tracking aviator fleet performance, such as safety check flights, re-qualification exams, upgrades and performance qualifications. It is recommended that a centralized methodology for tracking the performance and qualifications of pilots be developed, with the ability to measure trends in performance after the qualified pilot leaves flight school. This database would provide a useful source for measuring trends in pilot performance throughout the fleet, and give a way of tracking trends occurring in the pilot community. In addition, it would provide managers a possible way to identify problem aviators before they create a crisis.

Most important, however, is the need to follow up on the individuals included in this study for the purpose of tracking them throughout their careers. The pilots included in this study have only begun their obligated service requirement, and have therefore not reached major career decision points. Identification of trends in retention and promotion, as related to flight school experience, is an area of study that should be examined. At issue is whether or not those individuals who performed well in flight school, based upon their composite scores, along with their demographic background, display measurable trends that affect early promotion and retention likelihood. In short, can the results of this study be extended to the career of a pilot? A follow-up study to measure the promotion and retention rates for these individuals should be conducted as their career progresses.

APPENDIX A. COMBINED DATA FILE DESCRIPTIONS

Variable	Description	Data Type/code/notes
SSN	Social Security Number	Type: Character
CURRSTAT	Current Status	Type: Factor Code: ATTRITION COMPLETION
SEX	Sex	Type: Factor Code: M - Male F - Female
COMMDATE	Commissioning Date	Type: Date
AQT	Aviation Qualification Test	Type: Integer Code: 0 - 9 Test Score Results
FAR	Flight Aptitude Rating	Type: Integer Code: 0 - 9 Test Score Results
NASCNSS	NASC Standard Score (%)	Type: Double
FINALCOM	Final Composite Score	Type: Double
RACE	Race	Type: Factor Code: black white other
MAJOR	Undergraduate Major	Type: Factor Code: 0 - Non-Technical 1 - Technical 2 - Engineer Note: Derived from OPNAVINST 1530

ETHNIC	Ethnic Group	Type: Factor Code: Asian Hisp None Other
SOURCE	Commissioning Source	Type: Factor Code: OCS NROTC USNA
GPA	Grade Point Average	Type: Factor Code: 0 - Less than 3.20 GPA 1 - Greater than 3.20 GPA
MATH	Mathematics GPA	Type: Factor Code: 0 - Calculus Grade B or lower 1 - Calculus Grade B+ or better
PHYSICS	Physics GPA	Type: Factor Code: 0 - Physics Grade B or lower 1 - Physics Grade B+ or higher
COLLEGE	Rating of College Attended	Type: Factor Code: 0 - Attended Non-rated School 1 - Attended top ranked National or Liberal Arts College 2 - Attended USNA
NASCRAW	NASC Raw Score (%)	Type: Double
PFG	Primary Raw Flight Grade	Type: Double
PAG	Primary Raw Academic Grade (%)	Type: Double
PFSS	Primary Flight Standard Score (%)	Type: Double

PASS	Primary Academic Standard Score (%)	Type: Double
PIPELINE	Aircraft Type	Type: Factor Code: Helo Jet Prop

APPENDIX B. SUMMARY OF PILOT DATA

1. Data below include all members of the student aviator data set, including both attritions and completions.

```
      SSN              CURRSTAT   SEX          COMMDATE
 Length:      2612   ATTR: 468   F: 150      Min.:10960
  Class:      AsIs   COMP:2144   M:2462  1st Qu.:11840
   Mode:character                         Median:12380
                                            Mean:12420
                                         3rd Qu.:13010
                                            Max.:14230

      AQT                FAR              NASCNSS          FINALCOM
    Min.:3.000        Min.:3.000       Min.: 0.00       Min.:  0.0
 1st Qu.:5.000     1st Qu.:5.000    1st Qu.:47.00    1st Qu.:162.0
  Median:6.000      Median:7.000     Median:53.00     Median:193.0
    Mean:6.072        Mean:6.777       Mean:50.22       Mean:166.7
 3rd Qu.:7.000     3rd Qu.:8.000    3rd Qu.:57.00    3rd Qu.:215.4
    Max.:9.000        Max.:9.000       Max.:97.83       Max.:304.0

    RACE       MAJOR       ETHNIC        SOURCE       GPA      MATH
 Black: 122   0:1321    Asian:   59   NROTC:1235    :1576    :1576
 Other: 121   1: 304     Hisp: 118      OCS: 386   1: 316   1: 220
 White:2369   2: 987     None:1610     USNA: 991   0: 720   0: 816
                        Other: 825

 PHYSICS    COLLEGE       PIPELINE       NASCRAW             PFG
  :1576     0:1042         NPH:776      Min.: 0.00         Min.:0.000
 1: 303     1: 579         NPM:607   1st Qu.:57.82     1st Qu.:3.034
 0: 733     2: 991         NPJ:382    Median:91.00      Median:3.063
                           NPO:241      Mean:77.58         Mean:2.828
                           NPA:204   3rd Qu.:95.00     3rd Qu.:3.088
                           NPT:148      Max.:99.99         Max.:3.991
                       (Other):254                         NA's:9.000

      PAG                 PFSS             PASS          PIPELINE
    Min.:   0.00      Min.: 0.00        Min.: 0.0        :  56
 1st Qu.:  90.67   1st Qu.:41.00    1st Qu.:44.0    helo: 776
  Median:  94.00    Median:49.00     Median:52.0     jet:1029
    Mean:  87.53      Mean:45.85       Mean:48.1    prop: 751
 3rd Qu.:  96.27   3rd Qu.:56.00    3rd Qu.:59.0
    Max.:100.00       Max.:99.00       Max.:95.0
    NA's: 10.00       NA's:42.00       NA's:42.0
```

2. Data below include all members of the student aviator data set who have completed the entire training pipeline.

```
         SSN                  CURRSTAT    SEX          COMMDATE
Length:      2144           ATTR:    0    F: 120       Min.:10960
 Class:      AsIs           COMP:2144     M:2024    1st Qu.:11820
  Mode:character                                     Median:12200
                                                       Mean:12340
                                                    3rd Qu.:12930
                                                       Max.:13870

       AQT              FAR              NASCNSS          FINALCOM
   Min.:3.00         Min.:3.000         Min.:20.00        Min.: 90.0
1st Qu.:5.00      1st Qu.:6.000      1st Qu.:49.00     1st Qu.:181.0
 Median:6.00       Median:7.000       Median:53.00      Median:200.1
   Mean:6.13         Mean:6.928         Mean:52.75        Mean:201.2
3rd Qu.:7.00      3rd Qu.:9.000      3rd Qu.:57.00     3rd Qu.:220.6
   Max.:9.00         Max.:9.000         Max.:97.83        Max.:304.0

     RACE       MAJOR         ETHNIC          SOURCE       GPA        MATH
Black:   71    0:1036      Asian:   38    NROTC:1024      :1299      :1299
Other:   81    1: 247       Hisp:   89      OCS: 289    1: 252     1: 185
White:1992     2: 861       None:1349      USNA: 831    0: 593     0: 660
                           Other: 668

PHYSICS    COLLEGE      PIPELINE         NASCRAW             PFG
 :1299      0:837         NPH:733        Min.: 0.00        Min.:0.000
1: 249      1:476         NPM:571     1st Qu.:58.55     1st Qu.:3.046
0: 596      2:831         NPJ:360      Median:92.00      Median:3.069
                          NPA:190        Mean:80.05        Mean:3.055
                          NPT:138     3rd Qu.:95.58     3rd Qu.:3.092
                          NPE:137        Max.:99.99        Max.:3.991
                      (Other): 15

       PAG                PFSS              PASS         PIPELINE
   Min.:  0.00         Min.:17.00        Min.:17.0      helo:733
1st Qu.: 91.40      1st Qu.:44.00     1st Qu.:46.0       jet:703
 Median: 94.33       Median:51.00      Median:53.0      prop:708
   Mean: 92.63         Mean:50.83        Mean:51.9
3rd Qu.: 96.40      3rd Qu.:57.00     3rd Qu.:59.0
   Max.:100.00         Max.:99.00        Max.:95.0
```

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